Urban Roadway Traffic Information from Bluetooth Scanner System

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Abstract: Bluetooth MAC scanner (BMS) is an advanced technology and cost effective measure for traffic data collection. This system provides the MAC ID of individual Bluetooth device that occupied area within BMS communication zone. Travel time and speed which commonly considered as main indicators for representing traffic conditions among two BMS stations can be directly extracted by matching MAC ID gathered from those stations. However, raw data from BMS system is generally contained noises and outliers. For that reason, the robust methodology for developing accurate segment travel time is crucial task in traffic data development from BMS system. This article demonstrates the frameworks for constructing segment travel time information from BMS system and also proposes travel time prediction model using ANN with neighboring segments relationship as inputs. Result from observation points out the potential of using BMS system as traffic data collection approach. The advantage of integrating neighboring segments relationship in ANN model is confirmed by the significantly increasing of accuracy up to 50 % from the baseline model.

Keywords: Bluetooth, Urban Roadway, Arterial Road, Travel Time Prediction, Travel Time Estimation, Travel Time

1. INTRODUCTION

Research on real-time and forecasted traffic situations on urban road network has become challenging topics for traffic professionals, due to the complex, non-linear, non-stationary behavior and the disturbance from surrounding environment such as movement of pedestrian at crossing, traffic signals, intersections and access from sideway (Nantes *et al*., 2014). By knowing accurate real-time and future traffic conditions, road users can make more efficient decision in rerouting the ongoing trip or well-prepare their upcoming trips. Traffic operators can also be benefit from this information by improving their traffic controls and operational plans.

In urban context, the main difficulties for travel time study are not only from the complexity of travel time behavior itself, but the lacking of traffic data from road network are considered as one of the major issues. In the past decades, research on traffic states and travel times study have been focused on data collected from traditional inductive loop detectors and probe vehicles system. For instance, using data from single loop detector (Wei *et al*., 2012; Chen *et al.*, 2011; Coric *et al.*, 2011; Jin *et al.*, 2010; Dailey, 1999), dual loop system (Soriguera and Robuste, 2011; Rakha and Zhang, 2005), taxi probes (Herring *et al*., 2010; Wei *et al*., 2007), bus probes (Pu and Lin, 2009; Uno *et al*., 2009; Bejan *et al.*, 2010; Vanajakshi *et al.*, 2009), or test vehicles (Puangprakhon and Narupiti, 2015; Jiang *et al.*, 2009; Billings and Yang, 2006). Even though the aforementioned systems are regarded as efficient approaches in traffic data collection, the requirement of mathematical and theoretical assumptions in converting data from loop detectors to segment travel time and the low penetration rates of probe vehicle in reality are the main drawbacks of those systems, respectively.

Bluetooth MAC Scanner (BMS) is the new emerging technology for traffic data collection. The concept of BMS in traffic data collection is simple. It scans and records MAC-ID together with time stamped of the discoverable Bluetooth devices (BT) within its communication zone e.g. from BT signal from mobile phones, car navigation systems, etc. The travel time of each vehicle between two consecutive BMS locations can be directly determined by the difference of discovered time of the same MAC-ID at those stations. Previous research from Wang *et al*. (2011) showed the promising results in travel time estimation while using BMS system compared to the travel time recorded from Automatic License Plate Recognition (ALPR) devices on both freeway and urban road. Bhaskar et al. (2013) tested the BMS system on arterial roadway and showed the potential of BMS in providing urban traffic conditions.

On the issue of traffic states or travel time prediction, many researchers have attempted to develop various prediction approaches e.g. using regression models (Rice and Zwet, 2004) time series models (Billings and Yang, 2006), Kalman filtering models and artificial neural network (ANN). Studies from the past have demonstrated that ANNs models have the potential to predict travel time on urban roadways with highly complex and complicated traffic behaviors by providing the promising outcomes when sufficient historical data can be obtained (Yu et al., 2008). The main advantages of ANN models or data-driven approaches over other techniques are that they do not require extensive theoretical or traffic flow modeling, many software packages are available and ready to use, fast and easy to implement (Dougherty, 1995). Despite previous works have demonstrated the favorable prediction outcomes from ANN, the following drawbacks remain to be further studied; most of the research has been focused on freeways where traffic behavior is less complicated than urban roadways, the predicted travel time from various studies came from simulated data which cannot truthfully represent the complicated situation in reality, most of previous studies accounted only the effects of historical travel time of study segment which limit the models to be applied when travel time from previous intervals are unavailable.

This paper aims to develop the framework for travel time estimation on urban roadways using data collected from BMS system and also propose the technique for improving the accuracy of travel time prediction model by integrating the related information of study segment and neighboring segments (spatio-temporal) in the ANN models.

The paper begins with details of BMS system and the deployment locations, followed by definition of segment travel times and concepts of travel time estimation from Bluetooth data, framework for data cleansing and travel time estimation results, travel time prediction models and inputs, respectively. The results and main conclusions of the study are discussed last.

2. BLUETOOTH SCANNER SYSTEM

2.1 Bluetooth MAC Scanners (BMS) and Installation Locations

To capture Bluetooth MAC addresses from Bluetooth devices, the Bluetooth MAC Scanners (BMS) developed by the collaboration between Department of Civil Engineering Chulalongkorn University and Ecobz Thailand Co., ltd. with the capability to scan and record Bluetooth MAC addresses have been used in this study. Each of them comprises 5 main components which are main board (RASBERRY PI 2 Model 2), Bluetooth adapter (Parini-UD 100), antenna (TP link (9dBi), router (TP-Link 3020 with 3g aircard) and power supply as depicted in Figure 1.

In this study, totally 41 BMSs have been placed within the police box at the intersections on urban roadways in Bangkok CBD for the uninterrupted supply of power and to detect the Bluetooth signals within its communication zone which is approximately 100 meters from the BMS (as recommended for traffic applications by Bhaskar and Chung, 2013). In this zone, a vehicle can spend significant time due to the interruption from traffic signals. Travel profile of vehicle within this BMS zone is non-uniform and commonly comprises stop-and-go behavior before the stop-line and accelerating beyond stop-line. Installation locations of BMSs are depicted in Figure 2.

Figure 1. Bluetooth MAC scanner and installation place

Figure 2. Locations of Bluetooth MAC scanners in Bangkok CBD

2.2 Data Gathering System

In this research, the inquiry cycle for each BMS has been set up at 1 second which means BMS sends the inquiry messages and scans the replied signal from Bluetooth devices within its communication zone every 1 second. Data recorded from BMS system (MAC-ID, detected time, BMS number) was sent to store in server via 3g telecommunication network. The example of recorded data from BMS is illustrated in Table 1; the first column represents the record number, second column is MAC-ID of the Bluetooth device which has 48 bits long and comprises a sequence of twelve hexadecimal digits (six groups of two hexadecimal digits), third column is the detected time of BT devices, and forth column is the number of BMS which represent the location BMS on road network or intersection ID (as depicted in Figure 2).

Table 1. Data gathered from BMSs in Bangkok, Thailand

Number	MAC-ID	Detected Time	BT Scanners ID
1	AC:7A:4D:A3:E4:XX	4/2/2016 5:04:40	47
2	AC:7A:4D:A3:E4:XX	4/2/2016 5:04:41	47
3	AC:7A:4D:A3:E4:XX	4/2/2016 5:04:42	47
4	64:D4:BD:D8:71:XX	4/2/2016 5:04:42	47
5	64:D4:BD:D8:71:XX	4/2/2016 5:04:43	47
6	64:D4:BD:D8:71:XX	4/2/2016 5:04:46	47
7	AD:C5:EE:02:F5:XX	4/2/2016 5:04:42	16
8	AD:C5:EE:02:F5:XX	4/2/2016 5:04:43	16
9	00:1D:FD:07:B0:XX	4/2/2016 5:04:42	16
10	64:D4:BD:D8:71:XX	4/2/2016 5:04:49	47
.	.	.	.
.	.	.	.
.	.	.	.

Remarks: In column 2, the last two digits are blinded due to privacy concerns

3. TRAVEL TIME ESTIMATION FROM BLUETOOTH DATA

3.1 Travel Time Modeling from BMS Data

Travel time between two consecutive BMSs on urban roadway network can be categorized into three types as illustrated in Figure 3 (Bhaskar and Chung, 2013). Firstly, travel time from stop line of upstream to stop line of downstream segment (*S2S*) which theoretically considered as segment travel time. This type of travel time is governed by the delay only from downstream segment. However, it is difficult to detect S2S travel time from BMS system because BMS can only discover the device IDs within its communication zone but cannot locate the real position of those devices. Secondly, travel time from entrance to entrance of BMS zone (*En2En*), this travel time contains partial delay of both intersections and can be detected by BMS system from the difference between first recorded data in each BMS zone. Thirdly, travel time from exit to exit of BMS zone (*Ex2Ex*), this travel time is govern mostly by the delay from downstream section due to segment delay can mainly be generally observed in the area before stop line near the signal or intersection (except in the case of heavy congestion with very long queue). This type of travel time can be extracted from BMS data by considering the difference between last detected times of BT devices at each BMS and will be considered as segment travel time instead of *S2S* in this research.

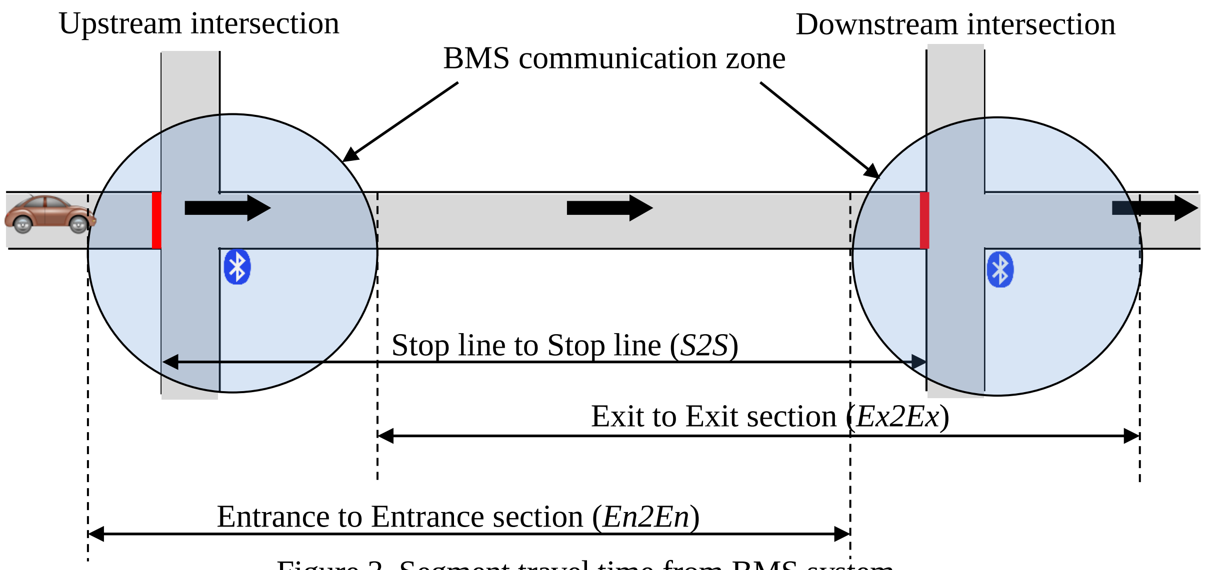


Figure 3. Segment travel time from BMS system

3.2 Framework for Extracting Travel Time from BMS Data

In this study BT data was collected from BMS system installed on urban roadway in Bangkok CBD. Details of recoded data are aforementioned in section 2.2. The framework for segment travel time estimation is depicted in Figure 4 which includes the following steps.

Data Matching: Due to each BT device can enter the same BMS zone multiple times per day therefore the trip exit-time of each BT device from BMS zone are need to be extracted. The 30 minutes time gap is set as the threshold to separate each trip which means the record is considered as last detected time of each trip at BMS when there are no other record from the same BT device can be discovered in that BMS zone within 30 minute from last detected time (in the case that record from same device is discovered at same BMS after 30 minute from last detected time it will be considered as another trip). Segment travel time or travel time from upstream to downstream BMSs can be calculated by the time difference of the same BT device recorded at those BMSs (*Ex2Ex* travel time).

Data Filtering: The objective of filtering process is to remove the questionable and outlier data from the samples. This process comprises 3 tasks as follows;

- Removing questionable ID: after the matching process travel times from questionable BT devices such as the cloned devices (from logistic company etc.) with same ID that can be found at several locations in the same time were removed.
- Removing questionable trips: this step aims at removing outlier trip by setting upper and lower boundaries for trip time to track the trip that faster and slower than usual trips. For instance, the trips those travel faster than speed limit available on roadways, or use another route instead of direct route between two BMSs, or from stopping vehicles.
- Removing outlier trips: by applying Median Absolute Deviation (MAD) method (Gather and Fried, 2004; Khoei, A. M. *et al*., 2013) which is a robust measure of the spread out of data.

  Let travel time values as univariate data, the MAD is the median of the absolute deviations from the data's median.

$$MAD = median \left| X_i - median(X) \right| \quad (1)$$

$$\sigma = k \cdot MAD \quad (2)$$

where k is a constant scale factor which depends on type of the distribution (in case of normal distribution k is taken to be 1.4826). In this research the 15 minutes moving time window was selected for calculating MAD. The suggested k value from previous study is from 1 to 5. For this study the k = 2 is applied in Eq. (2). The upper and lower boundaries for filtering outlier trips can be calculated by adding and subtracting σ from MAD. The trip travel times beyond these boundaries are considered as outlier values and removed.

Data Smoothing: This step aims to reduce or eliminate short-term volatility and extract real trends and patterns from travel time data by applying exponential smoothing.

$$s_t = \alpha y_t + (1-\alpha) s_{t-1}, \quad t > 0 \quad (3)$$

where s_t is the output of the exponential smoothing, α is the smoothing factor, y_t is recorded travel time at time t, $(1-\alpha)$ is the damping factor. In this study the α value of 0.55 was applied regarding its smallest mean square error regarding to the record in our database.

Travel time estimation: In this study we have divided time of day into 96 intervals (15 minutes per interval) from 0:00:00-0:14:59, 0:15:00-0:29:59, …, 23:45:00-23:59:59. The travel time for interval i (TT_i) can be calculated by averaging all the travel time of trips within that interval as follow:

$$TT_i = \frac{1}{n} \sum_{t=1}^{n} s_t \qquad \text{for } i = 1, 2, 3, ..., 96 \quad (4)$$

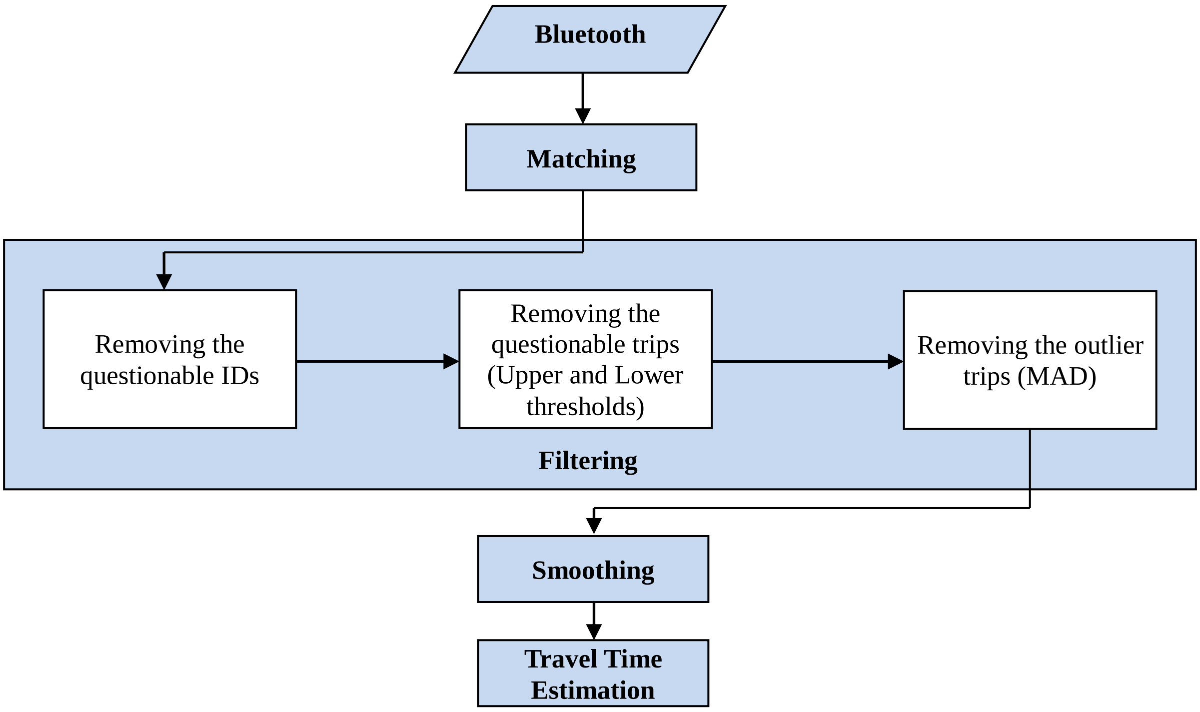


Figure 4. Framework for travel time estimation from BT data

3.3 Travel Time Estimation from Bluetooth Data

The *Ex2Ex* travel time (as described in section 3.1) for a segment from Phatumwan junction to Chareonphol junction is presented in Figure 5. Figure 5(a) and 5(b) depicts the raw data recorded from individual vehicle and the filtered data from proposed framework, respectively. Figure 5(c) presents the estimated travel time for each time interval (15 minutes/interval as mentioned in section 3.2). These results indicate the potential of BMS in providing travel time or traffic state information on urban road network.

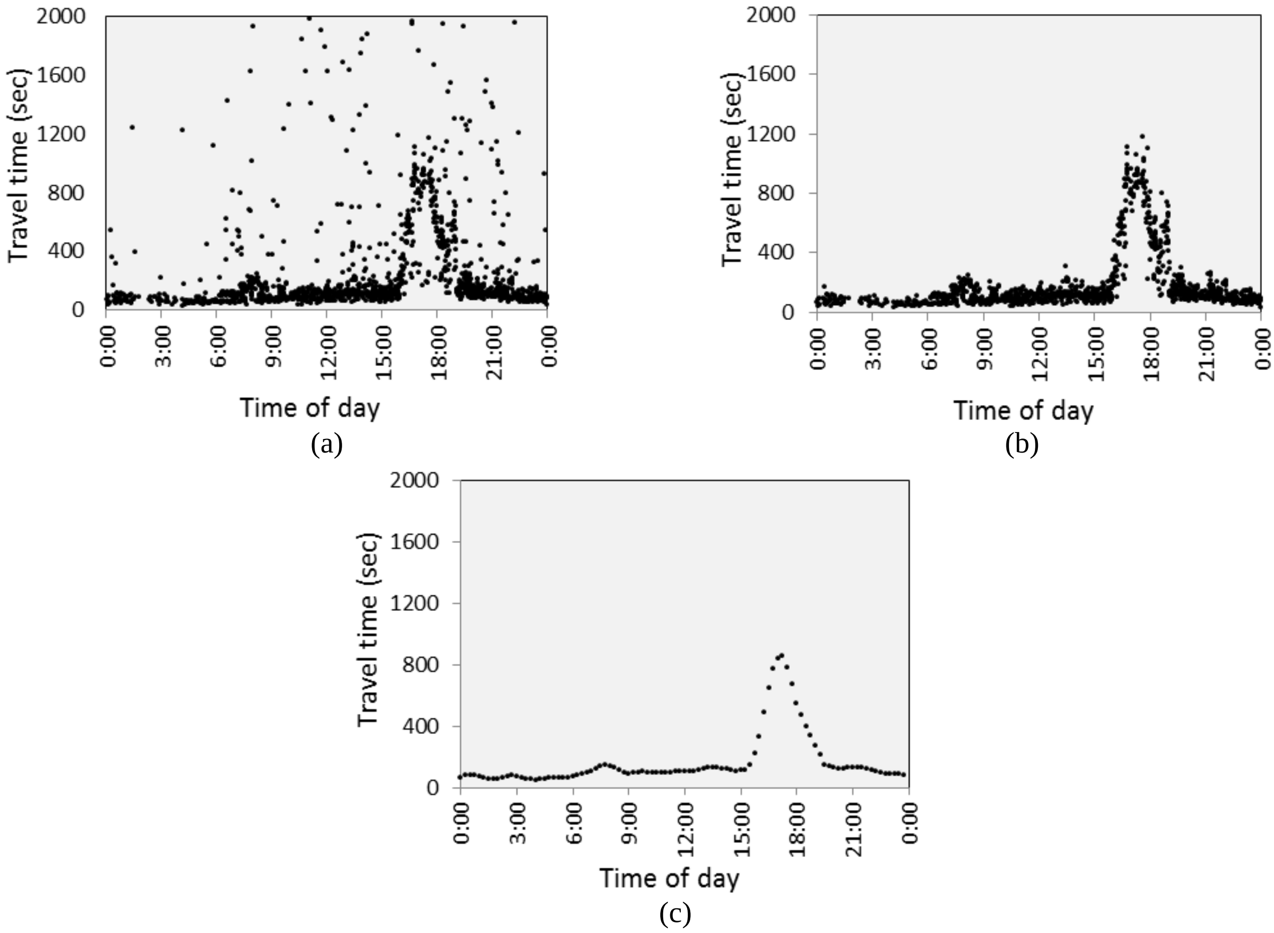


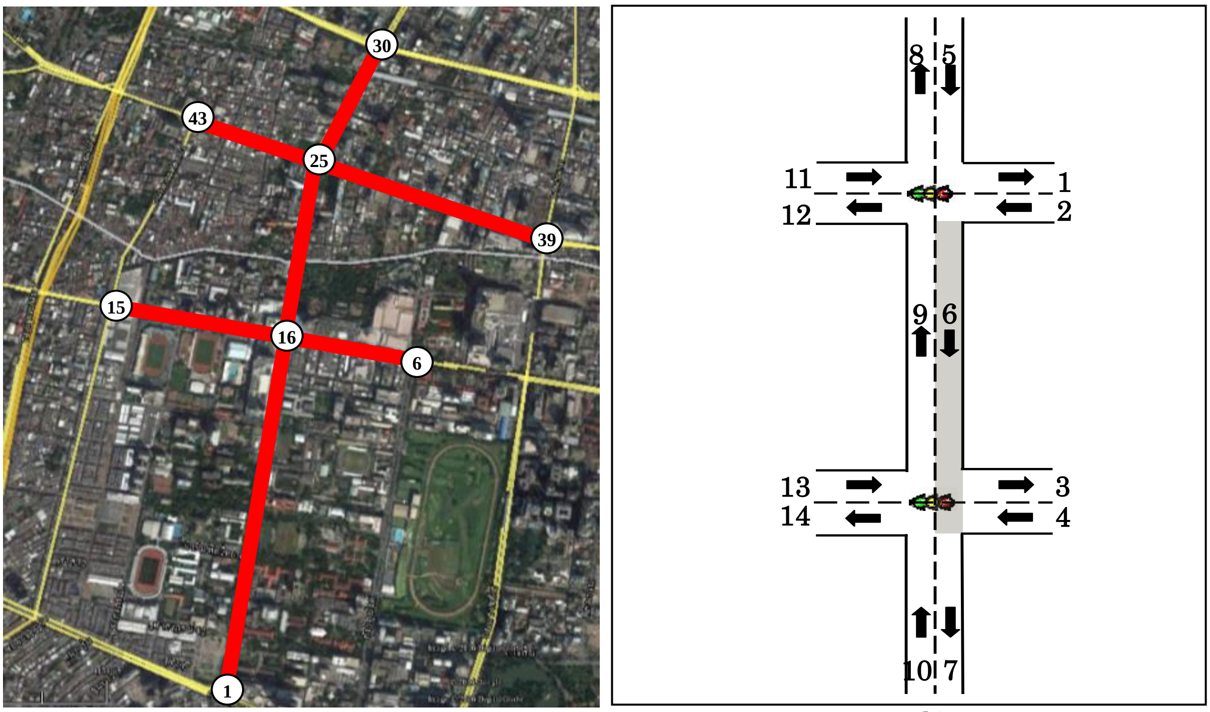
Figure 5. Travel time from BMS system (a) travel time before filtering (b) travel time after filtering (c) estimated travel time for each interval

4. TRAVEL TIME PREDICTION

Techniques for traffic prediction can be categorized into two main approaches: model based and data-driven approaches. However, most of previous works on urban roads applied data-driven approaches as their prediction techniques (Liu, H. *et al*, 2006) due to the limitation of model based approaches that requires many mathematical assumptions and site specific behavior. In this research, the data-driven, self-adaptive, and nonlinear methodology called Artificial Neural Network (ANN) will be chosen as the key technique for addressing travel time prediction problem on urban roadway.

4.1 Study Corridor

In our experiments, Bluetooth data collected from urban arterial roadway from February, 4 2016 to March 7, 2016 (33 days) in Bangkok CBD was used to test and verify the accuracy of proposed technique in addressing segment travel time prediction problem. The arterial roadway network comprises 7 segments partitioned at signalized intersection with different segment length ranging from 0.5 km to 1.49 km as illustrated in Figure 6(a) were selected as the study corridor. Number of lanes of each segment also varies, some have 3 lanes and others have 4 lanes per direction.



(a) (b)

Figure 6. (a) Study site (b) schematic diagram of signalized arterial roads

4.2 Modeling of Traffic on Urban Roadways

One of the key issues in modeling traffic using neural networks is the determination of suitable input and output pairs. In this research we have selected the output *Y(k)* as a scalar depicting segment travel time. The input *X(k)* were comprised three main groups; segment travel time from previous interval, neighboring segments travel time from previous interval, and time data (time of day, day of week)

Figure 6(b) illustrates the signalized arterial roads consist of 14 uni-directional road sections and two signalized intersections. If we consider the section number 6, its neighboring sections can be classified into two categories; which are the entrance and exit sections of the traffic flows of section 6 (in this case section 2, 5 and 11 are the entrance sections while section 3, 7 and 14 are exit sections. These neighboring sections will be carefully integrated into the travel time prediction model.

4.3 Artificial Neural Network (ANN) and Model Inputs

The feed-forward neural network with back propagation was selected as the key technique for prediction. Details of the ANN are depicted in Figure 7. The inputs for each prediction model including; travel time from previous time intervals of study segment, travel time from previous time intervals of neighboring segments, time of day, and day of week are summarized in Table 2. For investigation on the accuracy of prediction models and proposed techniques, the simplest ANN model with 1 input (Model 1) was treated as the baseline model and used to compare with others.

The Bluetooth data collected from 33 days (approximately 5 weeks) was separated into 2 groups; first group comprises data from 26 days was used in model training and learning process. The batch training with Levenberg-Marquardt algorithm that designed to minimizing a sum of square error function was selected in model training, second group comprise 7 days (1week) data was used to test the accuracy of prediction models.

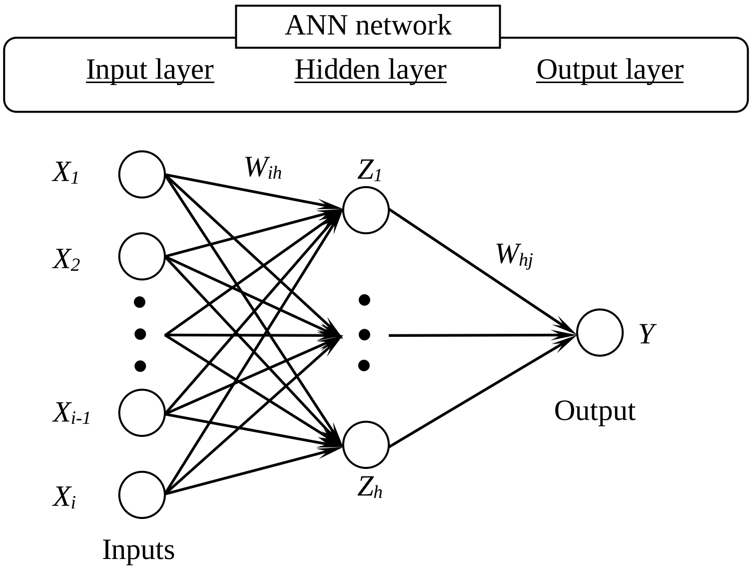


Figure 7. Topology of the neural network model for travel time prediction

Table 2. The inputs of travel time prediction models

Model(*)	Previous TT (Intervals)			Previous TT of Neighboring segments (Intervals)			Time of day	Day of week
	1	2	3	1	2	3		
1 (S1)	●							
2 (S2)	●	●						
3 (S3)	●	●	●					
4 (S1T)	●						●	
5 (S2T)	●	●					●	
6 (S3T)	●	●	●				●	
7 (S1TD)	●						●	●
8 (S2TD)	●	●					●	●
9 (S3TD)	●	●	●				●	●
10 (S1N)	●			●				
11 (S2N)	●	●		●	●			
12 (S3N)	●	●	●	●	●	●		
13 (S1NT)	●			●			●	
14 (S2NT)	●	●		●	●		●	
15 (S3NT)	●	●	●	●	●	●	●	
16 (S1NTD)	●			●			●	●
17 (S2NTD)	●	●		●	●		●	●
18 (S3NTD)	●	●	●	●	●	●	●	●

* terms in ( ) are describes as follows; S = study segment, 1-3 is number of previous time intervals, T = time of day, D = day of week, N = neighboring segments

4.4 Model Evaluation

In order to examine the accuracy of estimation model, the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were used to investigate the amount of estimation error compared with the observation since MAPE can express the estimation error in generic percentage terms and is often useful as the accuracy indicator while RMSE can measure the differences between estimated values and the values actually observed.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{x}(i) - x(i)\right| \tag{5}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{\hat{x}(i) - x(i)}{x(i)}\right| \tag{6}$$

$$RMSE = \sqrt{\frac{\sum(\hat{x}(i) - x(i))^2}{n}} \tag{7}$$

where $\hat{x}$ is the forecasted travel time, x denotes the observed travel time and n is the number of data to be computed.

Percentage of Improvement (*PoI*) was used to investigate of the performance of proposed method over the baseline model. The *PoI* of travel time prediction from proposed method related to the baseline method can be computed in terms of Root Mean Square Error (RMSE) by:

$$PoI = \frac{RMSE_{baseline} - RMSE_{proposed}}{RMSE_{baseline}} \times 100 \tag{8}$$

Typical *MAPE* value for performance assessment are illustrated in Table 3 (Lewis, C. D., 1982; Lee, Y., 2009).

Table 3. *MAPE* criterion for model evaluation

MAPE(%)	Assessment
<10	Highly accurate forecasting
10-20	Good forecasting
20-50	Reasonable forecasting
>50	Inaccurate forecasting

5. ACCURACY OF TRAVEL TIME PREDICTION FROM ANN MODELS

In this section, the performance and accuracy of proposed models in segment travel time prediction were investigated and compared with the baseline model (Model 1). Table 4 shows the comparison of results from 18 travel time prediction models.

Table 4. Accuracy of predictions

Models	*MAE*	*MAPE*	*RMSE*	*PoI* (%)	Assessment
1 (S1)	38.06	12.50	57.50	Baseline	Good forecasting
2 (S2)	21.04	7.54	31.85	44.61	Highly accurate forecasting
3 (S3)	**19.04***	**6.38***	29.42	48.84	Highly accurate forecasting
4 (S1T)	39.19	11.86	59.76	-3.92	Good forecasting
5 (S2T)	21.91	8.16	31.89	44.54	Highly accurate forecasting
6 (S3T)	20.47	7.20	31.31	45.55	Highly accurate forecasting
7 (S1TD)	41.24	13.06	60.82	-5.77	Good forecasting
8 (S2TD)	22.11	8.85	30.90	46.27	Highly accurate forecasting
9 (S3TD)	19.49	7.23	29.11	49.38	Highly accurate forecasting
10 (S1N)	44.15	16.40	63.08	-9.69	Good forecasting
11 (S2N)	24.70	9.10	41.09	28.55	Highly accurate forecasting
12 (S3N)	20.48	7.51	30.76	46.51	Highly accurate forecasting
13 (S1NT)	34.88	11.99	51.35	10.70	Good forecasting
14 (S2NT)	26.51	9.80	38.94	32.29	Highly accurate forecasting
15 (S3NT)	19.70	7.11	**28.75***	**50.00***	Highly accurate forecasting
16 (S1NTD)	45.45	19.93	60.04	-4.41	Good forecasting
17 (S2NTD)	25.10	8.97	43.14	24.99	Highly accurate forecasting
18 (S3NTD)	28.01	9.10	45.44	20.97	Highly accurate forecasting

* Best value from all models

As shown in Table 4, the models with highest forecasting accuracy identified by *MAE* and *MAPE* values is Model 3(3s) with 19.04 sec and 6.38% of *MAE* and *MAPE* respectively, while Model 15(S3NT) is the most accurate model based on *RMSE* and *PoI* values. On the other hand, models using only data from one previous interval (S1, S1T, S1TD, S1N, S1NT, S1NTD) as inputs underperform the models using inputs from more than one previous intervals which identified by the higher *MAE*, *MAPE* and *RMSE* values.

Assessment from *MAPE* indicates the models with input from one previous interval as “good forecasting” while model with inputs from more than one previous interval are classified as “highly accurate forecasting models”. This is due to the using of data from more than one previous interval could provide information of traffic trend to the model.

Including information of neighboring segments and time of day as inputs has potential in improving model accuracy as could be seen from *PoI* value of the best model (Model 15 (S3NT)) among 18 models that significantly improves the prediction accuracy up to 50% from baseline model.

Effect of the day of week on prediction accuracy is not clearly confirmed from test results although in most cases adding day of week as input lessens the forecasting accuracy. However it should be noted that in this study data from 26 days (approximately 4 weeks) was used in ANN training which could be not enough to extract the different traffic behavior among each day of week. Therefore, it is recommended for the future study that the bigger dataset should be used to test and confirm the effect of day of week on prediction accuracy.

6. CONCLUSIONS AND RECOMMENDATIONS

BMS is an emerging technology and considered as one of most cost effective techniques in traffic data collection. In this paper, we have demonstrated the framework for developing travel time information from BMS data and also proposed the travel time prediction model by using ANN approach with various combinations of inputs such as the neighboring segment relationship, the data from previous time intervals, time of day, etc.

Result from analysis indicates the potential of using BMS as traffic data collection technique and also point out the advantage of using ANN in travel time prediction in urban context with highly complex traffic behavior. The correctness of prediction also confirmed by model assessment with “Highly accurate forecasting” class in all models with inputs from more than one previous time intervals.

The input analysis shows the benefit from adding neighboring segment relationships and time of day as model inputs in travel time prediction by remarkable improving the accuracy from baseline model up to 50% (*PoI*). Effect of the day of week on prediction accuracy is not clearly confirmed from test results, the recommendation for the future study is to test this input with the larger and longer dataset.

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